

Unveiling the geography of historical patents in the United States from 1836 to 1975 - Replication example

Sergio Petralia, Pierre-Alexandre Balland & David Rigby

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Installing and loading Packages

```
install.packages('data.table')
install.packages('tm')
install.packages('stringi')
install.packages('plyr')
install.packages('RSNNS')
install.packages('neuralnet')
install.packages('kknns')
install.packages('plotly')
```

```
library(data.table)
library(tm)
library(stringi)
library(plyr)
library(RSNNS)
library(neuralnet)
library(kknns)
```

Load the data we will use in this tutorial

```
load("Example.RData")
```

```
ls()
```

```
[1] "Assignees"           "BTW"
[3] "Cities2Search"      "City.Data"
[5] "City.Matches"       "City.Names"
[7] "City.State.Data"    "Cutoff"
[9] "For"                 "Geography"
[11] "I"                   "ID"
[13] "Inventors"          "Keywords"
[15] "KNN"                 "KNN.Results"
[17] "KNN.Table"          "List"
[19] "NN"                  "NN.Results"
[21] "NN.Table"           "OCR.Documents"
[23] "Patents"            "Predicted.Geography"
[25] "Probit"              "Probit.Results"
[27] "Probit.Table"       "Replications.NN"
```

```

[29] "Retrieved.States.Abbreviations" "Retrieved.States.Names"
[31] "Sample"                          "SampleTR"
[33] "SampleTS"                        "State.Data"
[35] "State.Matches"                   "State.Names"
[37] "States2Search"                   "StatesAbb2Search"
[39] "Threshold"                       "X0"
[41] "XOTR"                            "XOTS"
[43] "Y.Hat"                           "Y.Hat.KNN"
[45] "Y.Hat.NN"

```

Step 1 - Identifying candidate locations

The first step consists of identifying candidate locations within the text documents. Before that, it is convenient to clean up the documents. We will need to create variables describing the locations, and as these variables are created evaluating the candidate locations within the context of the document it is convenient to reduce the size of the documents by trimming unnecessary words.

1.a Trimming Documents

The object “OCR.Documents” contain the documents we will use throughout the example

```
length(OCR.Documents)
```

```
[1] 8481
```

```
# Let's take a look at the 10th entry
head(OCR.Documents[10])
```

```
[1] "PATENTED APR PROCESS SYNTHESIS DRYING OILS PET BONS ROLEUM HYDRO ..."
```

This is a short version of the original patent. The original document can be found here: <https://www.google.com/patents/US2345754>. Evaluating possible locations in the original document will require to match candidate names with all words in the text, however, if we take advantage of the fact that locations are usually quoted containing with at least a capital letter, then we could disregard all the words that do not contain one. If we want to keep important words that often occur close to geographical locations we can first capitalize them. For a great tutorial on text mining see: <https://cran.r-project.org/web/packages/tm/vignettes/tm.pdf>. Notice that we removed numbers and punctuation, and uppercased all words.

1.b Preparing the city and state names to look for

We need a list of US city names to look through the documents

```
head(City.Names)
```

	City	State	FIPS	County
1	GREENE	OH	39155	TRUMBULL
2	CATSKILL	NY	36039	GREENE

```

3     NEW YORK    NY 36061 NEW YORK
4         KINGS    NY 36047    KINGS
5 KINGS COUNTY    NY 36047    KINGS
6         AKRON    OH 39153    SUMMIT

```

We create a character vector with a list of names to search over

```

Cities2Search=as.character(unique(City.Names$City))
Cities2Search=paste(' ',Cities2Search,' ',sep='')

```

We add a space after and before to make sure that we don't find words that are substrings of other words. We do the same for state names:

```

States2Search=as.character(unique(State.Names$Name))
States2Search=paste(' ',States2Search,' ',sep='')

StatesAbb2Search=as.character(unique(State.Names$Abbreviation))

```

Note: States are often quoted using the US postal code abbreviation of that time.

1.c Look for state names within the documents

```

Retrieved.States.Names=lapply(OCR.Documents,function(y)
  States2Search[stri_detect_fixed(y,States2Search)])
Retrieved.States.Abbreviations=lapply(OCR.Documents,function(y)
  StatesAbb2Search[stri_detect_fixed(y,StatesAbb2Search)])

```

Let's take a look

```
head(Retrieved.States.Names)
```

```
$US3693398
character(0)
```

```
$US3399321
character(0)
```

```
$US3413841
character(0)
```

```
$US1977249
character(0)
```

```
$US120714
[1] "MS"
```

```
$US1451635
[1] "WA"
```

You might want to create a Flag to differentiate whether the state was found with a complete name or just an abbreviation. Here we won't do that.

1.c Look for state names within the documents

```
Retrieved.States.Names = lapply(Retrieved.States.Names,  
  function(y) as.character(State.Names$State.Code[match(gsub("^\\s+|\\s+$", "", y),  
    State.Names$Name)]))  
Retrieved.States.Abbreviations=lapply(Retrieved.States.Abbreviations,  
  function(y) as.character(State.Names$State.Code[match(y,State.Names$Abbreviation)]))  
State.Matches=mapply(c, Retrieved.States.Names, Retrieved.States.Abbreviations,  
  SIMPLIFY=FALSE)
```

```
head(State.Matches)
```

```
$US3693398  
character(0)
```

```
$US3399321  
character(0)
```

```
$US3413841  
character(0)
```

```
$US1977249  
character(0)
```

```
$US120714  
[1] "MS"
```

```
$US1451635  
[1] "WA"
```

Note: Dont' forget to take the spaces out

1.d Look for city names within the documents (It may take several minutes)

```
City.Matches=lapply(OCR.Documents,  
  function(y) Cities2Search[stri_detect_fixed(y,Cities2Search,case_insensitive=F)] )
```

```
head(City.Matches)
```

```
$US3693398  
[1] " DENMARK " " LARSON " " METHOD " " SIDES " " SIGURD "
```

```
$US3399321  
[1] " LAWRENCE " " BUTLER " " COLLINS " " JAMES " " HENDERSON "  
[6] " METAL " " JULY " " EARTH "
```

```

$US3413841
[1] " JOHNSON "      " PRESTON "      " HENSLEY "      " SWITZERLAND "
[5] " SWISHER "      " STATION "      " WEBER "        " SIXTEEN "
[9] " JEFFREY "      " MCCOY "        " METHOD "        " SHORTLY "
[13] " PLASTIC "      " WALLS "        " BLACK "        " SMALL "
[17] " NOLTON "

```

```

$US1977249
[1] " VIEW "      " ROBERT "

```

```

$US120714
[1] " MONROE "      " MISSISSIPPI " " ABERDEEN "      " WATER "
[5] " CLEMMONS "

```

```

$US1451635
[1] " WASHINGTON "   " AUGUST "       " ABERDEEN "      " THOMAS "
[5] " HARBOR "       " JOSEPH "       " GRAYS HARBOR "

```

There are many false positives detected. To evaluate candidate locations we will use information about the inventor/assignee names whenever it is available.

```
head(Inventors)
```

	Publication.number	Inventors.E	Inventors
6257	US3693398	JOHANNES SIGURD PEDERSEN PEDERSEN	JOHANNES SIGURD
5588	US3399321	KAUER ERHARD	ERHARD KAUER
5626	US3413841	WEBER MAX	MAX WEBER
2381	US1977249	SPRAGINS ROBERT L	ROBERT L SPRAGINS
540	US120714	NA	ALVEUS J CLEMMTOTS
1105	US1451635	THOMAS JOSEPH	JOSEPH THOMAS

```
head(Assignees)
```

	Publication.number	Original.Assignee.E
1	US3693398	AARHUS METALEBALLAGE IND
2	US3399321	NORTH AMERICAN PHILIPS COMPANY INC
3	US3413841	ELCALOR AG
4	US1977249	SPRAGINS ROBERT L
5	US120714	NA
6	US1451635	JOSEPH THOMAS

	Original.Assignee
1	AARHUS METALEBALLAGE IND
2	PHILIPS CORP
3	ELCALOR AG
4	ROBERT L SPRAGINS
5	<NA>
6	JOSEPH THOMAS

This information is available at the Espacenet website, USPTO website, and on google patents. See: <https://www.google.com/patents/US3693398>, <http://patft.uspto.gov/netacgi/nph-Parser?Sect2=PTO1&Sect2=HITOFF&p=1&u=/netahtml/PTO/search-bool.html&r=1&f=G&l=50&d=PALL&RefSrch=yes&Query=PN/3693398> and: <http://worldwide.espacenet.com/publicationDetails/biblio?CC=US&NR=3693398A&KC=A&FT=D>

1.e We now create a database with characteristics of each located state name

We identify the documents with positive entries

```
I=apply(State.Matches,length)!=0
```

```
summary(I)
```

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	NA's
1	139	281	279	417	557	451

We create a list containing all the information for each documents (More appropriate in R)

```
List=mapply(function(x,y,r,z,t) list(x,y,r,z,t),OCR.Documents[I],State.Matches[I],
  paste(Assignees$Original.Assignee[I],Assignees$Original.Assignee.E[I],
  sep=','), paste(Inventors$Inventors[I],Inventors$Inventors.E[I],sep=','),
  Patents$Publication.number[I],SIMPLIFY = FALSE)
```

```
unlist(List[[1]])
```

```
[1] "DESCRIPTIONÂ   OCR ERRORS\nUNITED NSTATES ALVEUS CLEMMONS ABERDEEN MISSISSIPPI \nIMPROVEMENT WATER
[2] "MS"
[3] "NA,NA"
[4] "ALVEUS J CLEMMTOTS,NA"
[5] "US120714"
```

Some useful Keywords to associate with the geographical locations

```
Keywords=c('COMPANY','CORPORATION','ASSIGNOR','INVENTOR')
Cutoff=c(' FIG ',' FIGURE ','REFERENCES CITED')
```

The following function evaluates characteristics of each geographical location. It is an attempt to provide a fast but at the same time “readable” code. It could be made more efficient.

```
State.Data=lapply(List,function(z) {
  # Each (z) corresponds to a document, where the first element is the description, the
  # second the detected state, and so on.

  # How many times the state was found?
  Data=data.frame(count(stri_trans_toupper(z[[2]])),stringsAsFactors=F)
  colnames(Data)=c('State','Frequency')
  Data$State=as.character(Data$State)

  # Finding the state names
  temp=lapply(Data$State,function(y) State.Names[stri_detect_fixed
    (State.Names$State.Code,y),1:2])
```

```

# For each State we retrieve the position in the document, it can be
# found several times in the text
Location.S=lapply(temp,function(y) unlist(stri_locate_all_fixed(z[[1]],
  as.character(y),omit_no_match = T)))
Min.Location=sapply(Location.S,function(y) min(y,na.rm=T))
Max.Location=sapply(Location.S,function(y) max(y,na.rm=T))
Mean.Location=sapply(Location.S,function(y) mean(y,na.rm=T))
Median.Location=sapply(Location.S,function(y) median(y,na.rm=T))

# Find the Location of important words
Location=unlist(lapply(Keywords,function(y) unlist(stri_locate_all_fixed(z[[1]],
  y,omit_no_match = T))))
Min.Keywords=min(Location,na.rm=T)
Max.Keywords=max(Location,na.rm=T)
Mean.Keywords=mean(Location,na.rm=T)
Median.Keywords=median(Location,na.rm=T)

# Find the Location of important words
Location=unlist(lapply(Cutoff,function(y) unlist(stri_locate_all_fixed(z[[1]],
  y,omit_no_match = T))))
Min.Cutoff=min(Location,na.rm=T)

# Finding The Assignee location (first clean it )
Assig=sapply(stri_split_fixed(z[[3]],','),function (x) gsub("^\\s+|\\s+$", "",
  as.character(stripWhitespace(removeWords(x,c(stri_trans_toupper(letters)))))))
Assig=stripWhitespace(stri_replace_all_fixed(Assig, "[[:punct:]]", ""))

Location=unlist(lapply(Assig,function(y) unlist(stri_locate_all_fixed(z[[1]],
  y,omit_no_match = T))))
Min.Assignees=min(Location,na.rm=T)
Max.Assignees=max(Location,na.rm=T)
Mean.Assignees=mean(Location,na.rm=T)
Median.Assignees=median(Location,na.rm=T)

# Finding The Inventor location
# First clean it

Inv=sapply(stri_split_fixed(z[[4]],','),function (x) gsub("^\\s+|\\s+$", "",
  as.character(stripWhitespace(removeWords(x,c(stri_trans_toupper(letters),letters))))))
Inv=stripWhitespace(stri_replace_all_fixed(Inv, "[[:punct:]]", ""))

Location=unlist(lapply(Inv,function(y) unlist(stri_locate_all_fixed(z[[1]],
  y,omit_no_match = T))))
Min.Inv=min(Location,na.rm=T)
Max.Inv=max(Location,na.rm=T)
Mean.Inv=mean(Location,na.rm=T)
Median.Inv=median(Location,na.rm=T)

# Now lets look for some important words, like County, resident, etc.
# And evaluate their distance with respect to the located state name.
State.Locations=lapply(Location.S,function(y) outer(y,
  rowMeans(stri_locate_all_fixed(z[[1]], ' STATE ',omit_no_match = T)[[1]]),FUN='-'))
County.Locations=lapply(Location.S,function(y) outer(y,

```

```

    rowMeans(stri_locate_all_fixed(z[[1]], ' COUNTY ', omit_no_match = T)[[1]], FUN='-')
City.Locations=lapply(Location.S,function(y) outer(y,
    rowMeans(stri_locate_all_fixed(z[[1]], ' CITY ', omit_no_match = T)[[1]], FUN='-'))
Subject.Locations=lapply(Location.S,function(y) outer(y,
    rowMeans(stri_locate_all_fixed(z[[1]], 'SUBJECT', omit_no_match = T)[[1]], FUN='-'))
Resident.Locations=lapply(Location.S,function(y) outer(y,
    rowMeans(stri_locate_all_fixed(z[[1]], c('RESIDENT', 'RESIDING'),
    omit_no_match = T)[[1]], FUN='-'))
BIKT.Locations=lapply(Location.S,function(y) outer(y,
    rowMeans(stri_locate_all_fixed(z[[1]], 'BE IT KNOWN THAT',
    omit_no_match = T)[[1]], FUN='-'))

R.of.State=unlist(lapply(State.Locations,function(y) min(y[y>0])))
L.of.State=unlist(lapply(State.Locations,function(y) max(y[y<0])))
R.of.County=unlist(lapply(County.Locations,function(y) min(y[y>0])))
L.of.County=unlist(lapply(County.Locations,function(y) max(y[y<0])))
R.of.City=unlist(lapply(City.Locations,function(y) min(y[y>0])))
L.of.City=unlist(lapply(City.Locations,function(y) max(y[y<0])))
R.of.Res=unlist(lapply(Resident.Locations,function(y) min(y[y>0])))
L.of.Res=unlist(lapply(Resident.Locations,function(y) max(y[y<0])))
R.of.BIKT=unlist(lapply(BIKT.Locations,function(y) min(y[y>0])))
L.of.BIKT=unlist(lapply(BIKT.Locations,function(y) max(y[y<0])))

# Compile
Data=data.frame(Data,Publication.number=z[[5]],Min.Cutoff,
    L.of.BIKT,R.of.BIKT,R.of.State,L.of.State,
    R.of.County,L.of.County,R.of.City,L.of.City,
    L.of.Res,R.of.Res,Min.Location,Max.Location,
    Mean.Location,Median.Location,Min.Keywords,
    Max.Keywords,Mean.Keywords,Median.Keywords,
    Min.Inv,Max.Inv,Mean.Inv,Median.Inv,
    Min.Assignees,Max.Assignees,Mean.Assignees,
    Median.Assignees)

return(Data)
})

State.Data=rbindlist(State.Data)

head(State.Data)

```

```

State Frequency.State Publication.number Min.Cutoff.State
1 MS 1 US120714 226
2 WA 1 US1451635 424
3 KS 1 US957500 497
4 WA 1 US957500 497
5 KS 1 US189636 289
6 WA 1 US189636 289
L.of.BIKT.State R.of.BIKT.State R.of.State.State L.of.State.State
1 -Inf Inf Inf -Inf
2 -Inf Inf Inf -126
3 -Inf Inf 4 -161

```

4	-Inf	Inf	Inf	-276
5	-Inf	Inf	4	-112
6	-Inf	Inf	Inf	-168
	R.of.County.State	L.of.County.State	R.of.City.State	L.of.City.State
1	4.5	-109.5	26.5	-87.5
2	Inf	-106.5	Inf	-Inf
3	20.5	-144.5	Inf	-Inf
4	Inf	-259.5	Inf	-Inf
5	20.5	-95.5	Inf	-Inf
6	Inf	-151.5	Inf	-Inf
	L.of.Res.State	R.of.Res.State	Min.Location.State	Max.Location.State
1	-Inf	Inf	67	201
2	-89.5	Inf	223	232
3	-Inf	Inf	246	421
4	-Inf	Inf	127	136
5	-Inf	Inf	144	270
6	-Inf	Inf	84	93
	Mean.Location.State	Median.Location.State	Min.Keywords.State	
1	134.0	134.0	Inf	
2	227.5	227.5	414	
3	333.5	333.5	474	
4	131.5	131.5	474	
5	207.0	207.0	Inf	
6	88.5	88.5	Inf	
	Max.Keywords.State	Mean.Keywords.State	Median.Keywords.State	
1	-Inf	NaN	NA	
2	420	417.0	417.0	
3	493	483.5	483.5	
4	493	483.5	483.5	
5	-Inf	NaN	NA	
6	-Inf	NaN	NA	
	Min.Inv.State	Max.Inv.State	Mean.Inv.State	Median.Inv.State
1	Inf	-Inf	NaN	NA
2	200	604	402	402
3	219	639	429	429
4	219	639	429	429
5	Inf	-Inf	NaN	NA
6	Inf	-Inf	NaN	NA
	Min.Assignees.State	Max.Assignees.State	Mean.Assignees.State	
1	Inf	-Inf	NaN	
2	200	604	402	
3	219	639	429	
4	219	639	429	
5	Inf	-Inf	NaN	
6	Inf	-Inf	NaN	
	Median.Assignees.State			
1	NA			
2	402			
3	429			
4	429			
5	NA			
6	NA			

1.f Do the same for city names

```
head(City.Data)
```

	City	Freq	Length	Publication.number	Min.Cutoff	Min.Countries
1	DATA	1	894	US3693398	423	Inf
2	LARSON	1	894	US3693398	423	Inf
3	METHOD	2	894	US3693398	423	Inf
4	SIDES	2	894	US3693398	423	Inf
5	SIGURD	1	894	US3693398	423	Inf
6	DENMARK	2	894	US3693398	423	Inf

	Country.Name	Discard	Detected.Name	Date	Month	R.of.Corporation
1		0	0	0	0	Inf
2		0	0	0	0	Inf
3		0	0	0	0	Inf
4		0	0	0	0	Inf
5		0	1	1	0	Inf
6		1	0	0	0	Inf

	L.of.STREET	L.of.BIKT	R.of.BIKT	R.of.State	L.of.State	R.of.County
1	-44.5	-Inf	Inf	Inf	-Inf	Inf
2	-14.5	-Inf	Inf	Inf	-Inf	Inf
3	-49.5	-Inf	Inf	Inf	-Inf	Inf
4	-19.5	-Inf	Inf	Inf	-Inf	Inf
5	-63.5	-Inf	Inf	Inf	-Inf	Inf
6	-37.5	-Inf	Inf	Inf	-Inf	Inf

	L.of.County	R.of.City	L.of.City	L.of.Res	R.of.Res	R.of.Columbia
1	-Inf	Inf	-Inf	-Inf	Inf	Inf
2	-Inf	Inf	-Inf	-Inf	Inf	Inf
3	-Inf	Inf	-Inf	-Inf	Inf	Inf
4	-Inf	Inf	-Inf	-Inf	Inf	Inf
5	-Inf	Inf	-Inf	-Inf	Inf	Inf
6	-Inf	Inf	-Inf	-Inf	Inf	Inf

	L.of.Columbia	R.of.Washington	L.of.Washington	R.of.Planograph
1	-Inf	Inf	-Inf	Inf
2	-Inf	Inf	-Inf	Inf
3	-Inf	Inf	-Inf	Inf
4	-Inf	Inf	-Inf	Inf
5	-Inf	Inf	-Inf	Inf
6	-Inf	Inf	-Inf	Inf

	L.of.Planograph	Name.Similarity	Min.Location	Max.Location	Mean.Location
1	-Inf	4	251	254	252.5
2	-Inf	4	279	284	281.5
3	-Inf	5	62	444	253.0
4	-Inf	4	93	474	283.5
5	-Inf	0	118	123	120.5
6	-Inf	6	143	205	174.0

	Median.Location	Min.Keywords	Max.Keywords	Mean.Keywords	Median.Keywords
1	252.5	Inf	-Inf	NaN	NA
2	281.5	Inf	-Inf	NaN	NA
3	253.0	Inf	-Inf	NaN	NA
4	283.5	Inf	-Inf	NaN	NA
5	120.5	Inf	-Inf	NaN	NA

	174.0	Inf	-Inf	NaN	NA	
	Min.Inv	Max.Inv	Mean.Inv	Median.Inv	Min.Assignees	Max.Assignees
1	109	132	120.5	120.5	160	184
2	109	132	120.5	120.5	160	184
3	109	132	120.5	120.5	160	184
4	109	132	120.5	120.5	160	184
5	109	132	120.5	120.5	160	184
6	109	132	120.5	120.5	160	184
	Mean.Assignees	Median.Assignees				
1	172	172				
2	172	172				
3	172	172				
4	172	172				
5	172	172				
6	172	172				

1.g Now merge the data

```
City.State.Data=merge(data.frame(City.Data),
                      data.frame(unique(City.Names[,c(1:2)])),
                      by='City',allow.cartesian=TRUE)
colnames(State.Data)[-c(1,3)]=paste(colnames(State.Data)[-c(1,3)], 'State', sep = '.')
City.State.Data=merge(City.State.Data,State.Data,by=c('Publication.number','State'),
                      all.x=T)
```

```
head(City.State.Data)
```

	Publication.number	State	City	Freq	Length	Min.Cutoff	Min.Countries
1	US3693398	CA	LARSON	1	894	423	Inf
2	US3693398	CA	SIDES	2	894	423	Inf
3	US3693398	IA	DENMARK	2	894	423	Inf
4	US3693398	IL	DENMARK	2	894	423	Inf
5	US3693398	KS	DENMARK	2	894	423	Inf
6	US3693398	ME	DENMARK	2	894	423	Inf
	Country.Name	Discard	Detected.Name	Date	Month	R.of.Corporation	
1	0	0	0	0	0	0	Inf
2	0	0	0	0	0	0	Inf
3	1	0	0	0	0	0	Inf
4	1	0	0	0	0	0	Inf
5	1	0	0	0	0	0	Inf
6	1	0	0	0	0	0	Inf
	L.of.STREET	L.of.BIKT	R.of.BIKT	R.of.State	L.of.State	R.of.County	
1	-14.5	-Inf	Inf	Inf	-Inf	Inf	Inf
2	-19.5	-Inf	Inf	Inf	-Inf	Inf	Inf
3	-37.5	-Inf	Inf	Inf	-Inf	Inf	Inf
4	-37.5	-Inf	Inf	Inf	-Inf	Inf	Inf
5	-37.5	-Inf	Inf	Inf	-Inf	Inf	Inf
6	-37.5	-Inf	Inf	Inf	-Inf	Inf	Inf
	L.of.County	R.of.City	L.of.City	L.of.Res	R.of.Res	R.of.Columbia	
1	-Inf	Inf	-Inf	-Inf	Inf	Inf	Inf
2	-Inf	Inf	-Inf	-Inf	Inf	Inf	Inf

3	-Inf	Inf	-Inf	-Inf	Inf	Inf
4	-Inf	Inf	-Inf	-Inf	Inf	Inf
5	-Inf	Inf	-Inf	-Inf	Inf	Inf
6	-Inf	Inf	-Inf	-Inf	Inf	Inf
L.of.Columbia R.of.Washington L.of.Washington R.of.Planograph						
1	-Inf	Inf	-Inf	-Inf	Inf	Inf
2	-Inf	Inf	-Inf	-Inf	Inf	Inf
3	-Inf	Inf	-Inf	-Inf	Inf	Inf
4	-Inf	Inf	-Inf	-Inf	Inf	Inf
5	-Inf	Inf	-Inf	-Inf	Inf	Inf
6	-Inf	Inf	-Inf	-Inf	Inf	Inf
L.of.Planograph Name.Similarity Min.Location Max.Location Mean.Location						
1	-Inf	4	279	284	281.5	
2	-Inf	4	93	474	283.5	
3	-Inf	6	143	205	174.0	
4	-Inf	6	143	205	174.0	
5	-Inf	6	143	205	174.0	
6	-Inf	6	143	205	174.0	
Median.Location Min.Keywords Max.Keywords Mean.Keywords Median.Keywords						
1	281.5	Inf	-Inf	NaN	NA	
2	283.5	Inf	-Inf	NaN	NA	
3	174.0	Inf	-Inf	NaN	NA	
4	174.0	Inf	-Inf	NaN	NA	
5	174.0	Inf	-Inf	NaN	NA	
6	174.0	Inf	-Inf	NaN	NA	
Min.Inv Max.Inv Mean.Inv Median.Inv Min.Assignees Max.Assignees						
1	109	132	120.5	120.5	160	184
2	109	132	120.5	120.5	160	184
3	109	132	120.5	120.5	160	184
4	109	132	120.5	120.5	160	184
5	109	132	120.5	120.5	160	184
6	109	132	120.5	120.5	160	184
Mean.Assignees Median.Assignees Frequency.State Min.Cutoff.State						
1	172	172	NA	NA		
2	172	172	NA	NA		
3	172	172	NA	NA		
4	172	172	NA	NA		
5	172	172	NA	NA		
6	172	172	NA	NA		
L.of.BIKT.State R.of.BIKT.State R.of.State.State L.of.State.State						
1	NA	NA	NA	NA		
2	NA	NA	NA	NA		
3	NA	NA	NA	NA		
4	NA	NA	NA	NA		
5	NA	NA	NA	NA		
6	NA	NA	NA	NA		
R.of.County.State L.of.County.State R.of.City.State L.of.City.State						
1	NA	NA	NA	NA		
2	NA	NA	NA	NA		
3	NA	NA	NA	NA		
4	NA	NA	NA	NA		
5	NA	NA	NA	NA		
6	NA	NA	NA	NA		
L.of.Res.State R.of.Res.State Min.Location.State Max.Location.State						

1	NA	NA	NA	NA
2	NA	NA	NA	NA
3	NA	NA	NA	NA
4	NA	NA	NA	NA
5	NA	NA	NA	NA
6	NA	NA	NA	NA
	Mean.Location.State	Median.Location.State	Min.Keywords.State	
1	NA	NA	NA	
2	NA	NA	NA	
3	NA	NA	NA	
4	NA	NA	NA	
5	NA	NA	NA	
6	NA	NA	NA	
	Max.Keywords.State	Mean.Keywords.State	Median.Keywords.State	
1	NA	NA	NA	
2	NA	NA	NA	
3	NA	NA	NA	
4	NA	NA	NA	
5	NA	NA	NA	
6	NA	NA	NA	
	Min.Inv.State	Max.Inv.State	Mean.Inv.State	Median.Inv.State
1	NA	NA	NA	NA
2	NA	NA	NA	NA
3	NA	NA	NA	NA
4	NA	NA	NA	NA
5	NA	NA	NA	NA
6	NA	NA	NA	NA
	Min.Assignees.State	Max.Assignees.State	Mean.Assignees.State	
1	NA	NA	NA	
2	NA	NA	NA	
3	NA	NA	NA	
4	NA	NA	NA	
5	NA	NA	NA	
6	NA	NA	NA	
	Median.Assignees.State			
1	NA			
2	NA			
3	NA			
4	NA			
5	NA			
6	NA			

Step 2 - Identify the correct locations

2.a Match the data with the collected sample

We can now match the data with the collected sample and create a flag identifying the correct locations

```
head(Sample)
```

```
Publication.number    City State Freq Length Min.Cutoff Min.Countries
```

1	US3693398	DENMARK	IA	2	894	423	Inf
2	US3693398	DENMARK	IL	2	894	423	Inf
3	US3693398	DENMARK	KS	2	894	423	Inf
4	US3693398	DENMARK	ME	2	894	423	Inf
5	US3693398	DENMARK	NY	2	894	423	Inf
6	US3693398	DENMARK	SC	2	894	423	Inf

	Country.Name	Discard	Detected.Name	Date	Month	R.of.Corporation	
1		1	0	0	0	0	Inf
2		1	0	0	0	0	Inf
3		1	0	0	0	0	Inf
4		1	0	0	0	0	Inf
5		1	0	0	0	0	Inf
6		1	0	0	0	0	Inf

	L.of.STREET	L.of.BIKT	R.of.BIKT	R.of.State	L.of.State	R.of.County	
1	-37.5	-Inf	Inf	Inf	-Inf	Inf	Inf
2	-37.5	-Inf	Inf	Inf	-Inf	Inf	Inf
3	-37.5	-Inf	Inf	Inf	-Inf	Inf	Inf
4	-37.5	-Inf	Inf	Inf	-Inf	Inf	Inf
5	-37.5	-Inf	Inf	Inf	-Inf	Inf	Inf
6	-37.5	-Inf	Inf	Inf	-Inf	Inf	Inf

	L.of.County	R.of.City	L.of.City	L.of.Res	R.of.Res	R.of.Columbia	
1	-Inf	Inf	-Inf	-Inf	Inf	Inf	Inf
2	-Inf	Inf	-Inf	-Inf	Inf	Inf	Inf
3	-Inf	Inf	-Inf	-Inf	Inf	Inf	Inf
4	-Inf	Inf	-Inf	-Inf	Inf	Inf	Inf
5	-Inf	Inf	-Inf	-Inf	Inf	Inf	Inf
6	-Inf	Inf	-Inf	-Inf	Inf	Inf	Inf

	L.of.Columbia	R.of.Washington	L.of.Washington	R.of.Planograph	
1	-Inf	Inf	-Inf	Inf	Inf
2	-Inf	Inf	-Inf	Inf	Inf
3	-Inf	Inf	-Inf	Inf	Inf
4	-Inf	Inf	-Inf	Inf	Inf
5	-Inf	Inf	-Inf	Inf	Inf
6	-Inf	Inf	-Inf	Inf	Inf

	L.of.Planograph	Name.Similarity	Min.Location	Max.Location	Mean.Location	
1	-Inf	6	143	205	174	
2	-Inf	6	143	205	174	
3	-Inf	6	143	205	174	
4	-Inf	6	143	205	174	
5	-Inf	6	143	205	174	
6	-Inf	6	143	205	174	

	Median.Location	Min.Keywords	Max.Keywords	Mean.Keywords	Median.Keywords	
1	174	Inf	-Inf	NaN	NA	
2	174	Inf	-Inf	NaN	NA	
3	174	Inf	-Inf	NaN	NA	
4	174	Inf	-Inf	NaN	NA	
5	174	Inf	-Inf	NaN	NA	
6	174	Inf	-Inf	NaN	NA	

	Min.Inv	Max.Inv	Mean.Inv	Median.Inv	Min.Assignees	Max.Assignees	
1	109	132	120.5	120.5	160	184	
2	109	132	120.5	120.5	160	184	
3	109	132	120.5	120.5	160	184	
4	109	132	120.5	120.5	160	184	
5	109	132	120.5	120.5	160	184	

6	109	132	120.5	120.5	160	184
	Mean.Assignees	Median.Assignees	Frequency.State	Min.Cutoff.State		
1		172	172	NA	NA	
2		172	172	NA	NA	
3		172	172	NA	NA	
4		172	172	NA	NA	
5		172	172	NA	NA	
6		172	172	NA	NA	
	L.of.BIKT.State	R.of.BIKT.State	R.of.State.State	L.of.State.State		
1		NA	NA	NA	NA	
2		NA	NA	NA	NA	
3		NA	NA	NA	NA	
4		NA	NA	NA	NA	
5		NA	NA	NA	NA	
6		NA	NA	NA	NA	
	R.of.County.State	L.of.County.State	R.of.City.State	L.of.City.State		
1		NA	NA	NA	NA	
2		NA	NA	NA	NA	
3		NA	NA	NA	NA	
4		NA	NA	NA	NA	
5		NA	NA	NA	NA	
6		NA	NA	NA	NA	
	L.of.Res.State	R.of.Res.State	Min.Location.State	Max.Location.State		
1		NA	NA	NA	NA	
2		NA	NA	NA	NA	
3		NA	NA	NA	NA	
4		NA	NA	NA	NA	
5		NA	NA	NA	NA	
6		NA	NA	NA	NA	
	Mean.Location.State	Median.Location.State	Min.Keywords.State			
1		NA	NA	NA		
2		NA	NA	NA		
3		NA	NA	NA		
4		NA	NA	NA		
5		NA	NA	NA		
6		NA	NA	NA		
	Max.Keywords.State	Mean.Keywords.State	Median.Keywords.State			
1		NA	NA	NA		
2		NA	NA	NA		
3		NA	NA	NA		
4		NA	NA	NA		
5		NA	NA	NA		
6		NA	NA	NA		
	Min.Inv.State	Max.Inv.State	Mean.Inv.State	Median.Inv.State		
1		NA	NA	NA	NA	
2		NA	NA	NA	NA	
3		NA	NA	NA	NA	
4		NA	NA	NA	NA	
5		NA	NA	NA	NA	
6		NA	NA	NA	NA	
	Min.Assignees.State	Max.Assignees.State	Mean.Assignees.State			
1		NA	NA	NA		
2		NA	NA	NA		
3		NA	NA	NA		

4	NA			NA		NA	
5	NA			NA		NA	
6	NA			NA		NA	
	Median.Assignees.State	Correct	Year	SUBSTRING	IS.WASH.ALSO	IS.COL.ALSO	
1	NA	0	1972	0	0	0	
2	NA	0	1972	0	0	0	
3	NA	0	1972	0	0	0	
4	NA	0	1972	0	0	0	
5	NA	0	1972	0	0	0	
6	NA	0	1972	0	0	0	
	COC						
1	0						
2	0						
3	0						
4	0						
5	0						
6	0						

At this stage we added some other useful variables. For instance, the variable COC identifies whenever a particular location name corresponded to the same county for another location within the same patent. Therefore it measures the co-occurrence of a county by two different location names in a patent.

2.b Create a function to use in the estimation

We create a function to use in the estimation. It will be handy so we don't have to create new variables when estimating different specifications

```
BTW=function(x,l,u) {y=1*I(as.numeric(x)>l & as.numeric(x)<u)
y[is.na(y)]=0
return(y)
}
```

It returns a number 1, for any vector x, whenever the value of an entry is between a lower value (l) and an upper value (u), and zero otherwise.

2.c Divide the sample into training and an evaluation set, by patent number

```
set.seed(1)
ID <- sample(1:2, length(unique(Sample$Publication.number)), replace = TRUE)
ID=ID[match(Sample$Publication.number,unique(Sample$Publication.number))]

SampleTR=Sample[ID==1,]
SampleTS=Sample[ID==2,]
```

2.d Estimating a Probit Model

```

Probit=glm(Correct~poly(Min.Location,5,raw=T)+BTW(L.of.STREET,-2,0)
+I(BTW(Min.Location-Min.Location.State,50,10000) |
  BTW(Min.Location.State-Min.Location,50,10000))+I(Min.Countries!='Inf')
+BTW(Min.Countries-Min.Location,0,15)
+I(BTW(Min.Location.State-Min.Cutoff,0,10000))==1 &
  I(Min.Location.State/Length)>0.5)
+I(BTW(Min.Location-Min.Cutoff,0,10000))==1 & I(Min.Location/Length)>0.5)
+COC+BTW(R.of.Corporation,0,10)+BTW(R.of.State,0,10)
+ Country.Name+SUBSTRING+factor(nchar(City))
+BTW(Min.Location.State-Min.Location,0,10)
+BTW(Min.Location-Min.Location.State,0,50)
+I(BTW(Min.Location.State-Min.Location,0,10) & I(Min.Location/Length)>0.5)
+I(BTW(Min.Location-Min.Location.State,0,50) & I(Min.Location/Length)>0.5)
+Detected.Name+Discard+is.na(Min.Location.State)
+poly(Min.Location/Length,5,raw=T)
+as.numeric(Max.Location/Length)+BTW(R.of.City,0,15)
+BTW(R.of.County,0,15)+I(BTW(R.of.City,0,15) | BTW(R.of.County,0,15))
+ BTW(Min.Location-Min.Keywords,-40,40)
+ I(I((is.na(Min.Location.State)))
  & BTW(Min.Location-Min.Keywords,-40,40)) ,data=SampleTR,
  family = binomial(link = "probit"))
Y.Hat= predict(Probit,newdata=SampleTS,type='response')

```

It proves to be useful to include covariates of competing candidate locations within a patent documents (as in a spatial econometrics framework).

```

# Assesment
Probit.Table=table(SampleTS$Correct,1*(Y.Hat>0.5))
colnames(Probit.Table)=c('Predicted as Incorrect (Y.Hat<0.5)',
  'Predicted as Correct (Y.Hat>0.5)')
row.names(Probit.Table)=c('Incorrect','Correct')

```

Probit.Table

	Predicted as Incorrect (Y.Hat<0.5)
Incorrect	175572
Correct	862

	Predicted as Correct (Y.Hat>0.5)
Incorrect	654
Correct	3904

2.d Lets normalize the data for the KNN and NN procedures (It may take several minutes)

```

X0=model.frame(Probit$formula,SampleTR)
X0=as.matrix(X0)
X0[X0=="FALSE" | X0==" FALSE"]='0'
X0[X0=="TRUE" | X0==" TRUE"]='1'
X0=apply(X0,2,function(y) as.numeric(y))
X0=normalizeData(X0, type = "0_1")
X0TR=data.frame(X0)

X0=model.frame(Probit$formula,SampleTS)
X0=as.matrix(X0)
X0[X0=="FALSE" | X0==" FALSE"]='0'
X0[X0=="TRUE" | X0==" TRUE"]='1'
X0=apply(X0,2,function(y) as.numeric(y))
X0=normalizeData(X0, type = "0_1")
X0TS=data.frame(X0)

```

2.e Estimating a KNN Model (It may take several minutes)

```

# Note: the results are already in the environment
For=paste(colnames(X0TR[,-1]),collapse='+')
KNN <- kknnpaste('X1~',For,collapse=''),train=X0TR,test=X0TS,
          k=10,scale=F,kernel='epanechnikov')
Y.Hat.KNN=KNN[[1]]

# Assesment
KNN.Table=table(SampleTS$Correct,1*(Y.Hat.KNN>0.5))
colnames(KNN.Table)=c('Predicted as Incorrect (Y.Hat<0.5)',
                      'Predicted as Correct (Y.Hat>0.5)')
row.names(KNN.Table)=c('Incorrect','Correct')

```

KNN.Table

	Predicted as Incorrect (Y.Hat<0.5)	
Incorrect		175465
Correct		844
	Predicted as Correct (Y.Hat>0.5)	
Incorrect		761
Correct		3922

2.f Estimating a NN Model (It may take several hours)

```

For=paste(colnames(X0TR[,-1]),collapse='+')

NN <- neuralnet(paste('X1~',For,collapse=''),data=X0TR,hidden=15,

```

```

        linear.output = F)
# Note: the results are already in the environment

Y.Hat.NN=compute(NN,covariate=XOTS[, -1])$net.result

# Assesment
NN.Table=table(SampleTS$Correct,1*(Y.Hat.NN>0.5))
colnames(NN.Table)=c('Predicted as Incorrect (Y.Hat<0.5)',
                    'Predicted as Correct (Y.Hat>0.5)')
row.names(NN.Table)=c('Incorrect', 'Correct')

```

```

NN.Table

```

	Predicted as Incorrect (Y.Hat<0.5)
Incorrect	175616
Correct	971

	Predicted as Correct (Y.Hat>0.5)
Incorrect	610
Correct	3795

Step 3 - Graphic Analysis

The results will slightly differ compared to the paper, as we are using a simplified specification.

3.a Create measures of Alpha and Coverage for each procedure

```

Threshold=seq(0.01,0.99,0.01)

# Probit Model
Probit.Results=lapply(Threshold,function(y){
  temp=table(SampleTS$Correct,1*(Y.Hat>y))
  Alpha=temp[1,2]/sum(temp[,2])
  Coverage=temp[2,2]/sum(temp[,2])
  return(data.frame(Threshold=y,Alpha=Alpha,Coverage=Coverage))
})
Probit.Results=rbindlist(Probit.Results)

# KNN Model
KNN.Results=lapply(Threshold,function(y){
  temp=table(SampleTS$Correct,1*(Y.Hat.KNN>y))
  Alpha=temp[1,2]/sum(temp[,2])
  Coverage=temp[2,2]/sum(temp[,2])
  return(data.frame(Threshold=y,Alpha=Alpha,Coverage=Coverage))
})
KNN.Results=rbindlist(KNN.Results)

```

```

# NN Model
NN.Results=lapply(Threshold,function(y){
  temp=table(SampleTS$Correct,1*(Y.Hat.NN>y))
  Alpha=temp[1,2]/sum(temp[,2])
  Coverage=temp[2,2]/sum(temp[2,])
  return(data.frame(Threshold=y,Alpha=Alpha,Coverage=Coverage))
})
NN.Results=rbindlist(NN.Results)

```

3.b Performance of Models

```

par(mfrow=c(1,3))

plot(Probit.Results$Threshold,Probit.Results$Coverage,
     main='Probit Model | Coverage and Alpha',ylab='',
     xlab='Threshold',type='l',lwd=3,bty='l',
     col='dodgerblue4',cex.main=1.5,cex.axis=1,cex.lab=1.5,ylim=c(0,1))
abline(h=0.05,col='black')
lines(Probit.Results$Threshold,Probit.Results$Alpha,
      ylab='',type='l',lwd=3,bty='l',col='red')
legend('topright',legend=c('Coverage','Alpha'),bty='n',lwd = 2,
      col = c('dodgerblue4','red'))

plot(KNN.Results$Threshold,KNN.Results$Coverage,
     main='KNN Model | Coverage and Alpha',ylab='',xlab='Threshold',
     type='l',lwd=3,bty='l',
     col='dodgerblue4',cex.main=1.5,cex.axis=1,cex.lab=1.5,ylim=c(0,1))
abline(h=0.05,col='black')
lines(KNN.Results$Threshold,KNN.Results$Alpha,ylab='',type='l',lwd=3,
      bty='l',col='red')
legend('topright',legend=c('Coverage','Alpha'),bty='n',lwd = 2,
      col = c('dodgerblue4','red'))

plot(NN.Results$Threshold,NN.Results$Coverage,
     main='NN Model | Coverage and Alpha',ylab='',xlab='Threshold',type='l',lwd=3,bty='l',
     col='dodgerblue4',
     cex.main=1.5,cex.axis=1,cex.lab=1.5,ylim=c(0,1))
abline(h=0.05,col='black')
lines(NN.Results$Threshold,NN.Results$Alpha,ylab='',type='l',lwd=3,
      bty='l',col='red')
legend('topright',legend=c('Coverage','Alpha'),bty='n',lwd = 2,
      col = c('dodgerblue4','red'))

```

3.c Performance comparison across models

```

par(mfrow=c(1,1))
plot(Probit.Results$Alpha,Probit.Results$Coverage,
     main='Comparison Across Models',ylab='Coverage',

```

```

    xlab='Alpha', type='l',lwd=3,bty='l',col='dodgerblue4',
    cex.main=1.5,cex.axis=1,cex.lab=1.5,ylim=c(0,1))
lines(KNN.Results$Alpha,KNN.Results$Coverage,ylab='',type='l',
      lwd=3,bty='l',col='red')
lines(NN.Results$Alpha,NN.Results$Coverage,ylab='',type='l',
      lwd=3,bty='l',col='dark green')
legend('bottomright',legend=c('Probit','KNN','NN'),bty='n',
      lwd = 3,
      col = c('dodgerblue4','red','dark green'))

```

3.d Geographical Distribution

```

library('plotly')

Geography=unique(subset(Sample,Correct==1)[,1:3])
Geography=merge(Geography,City.Names,by=c('City','State'))
Geography$Place=paste(Geography$County,Geography$State,sep = ' | ')
Geography=count(Geography,'Place')
Geography=Geography[order(Geography$freq,decreasing = T),]

Predicted.Geography=unique(subset(SampleTS,Y.Hat>0.75)[,1:3])
Predicted.Geography=merge(Predicted.Geography,City.Names,
                          by=c('City','State'))
Predicted.Geography$Place=paste(Predicted.Geography$County,
                               Predicted.Geography$State,sep = ' | ')
Predicted.Geography=count(Predicted.Geography,'Place')
I=match(Geography$Place,Predicted.Geography$Place)
Predicted.Geography=Predicted.Geography[I,]
Predicted.Geography$freq[is.na(Predicted.Geography$freq)]=0
Predicted.Geography$Place=Geography$Place

```

Plot with all the Values

```

plot_ly(x=Geography$Place , y = Geography$freq/sum(Geography$freq),
        type = "bar",opacity = 0.9,name='Sample') %>%
  add_trace(x=Predicted.Geography$Place,
            y = Predicted.Geography$freq/sum(Predicted.Geography$freq),
            type = "bar",opacity = 0.6,name='Predicted') %>%
  layout(barmode='overlay', showlegend = T,xaxis = list(title=' ',
    autotick = T,showticklabels = FALSE,tickcolor = toRGB("white"))
    , yaxis = list(title='Distribution'))

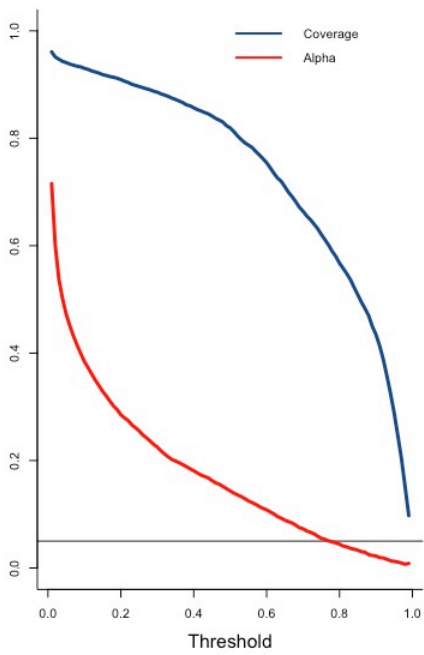
```

Note that NY is highly under-represented in the final sample. In the original code we included specific variables for cities which their name coincide with the name of the state. This improved the accuracy drastically.

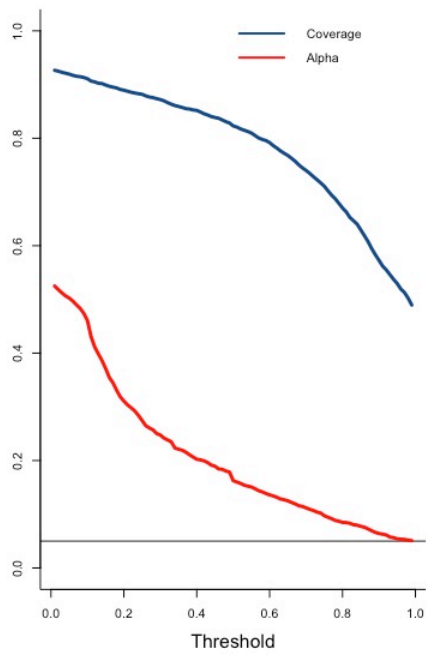
Plot with only positive Values

```
plot_ly(x=Geography$Place[Predicted.Geography$freq>0] ,
        y = Geography$freq[Predicted.Geography$freq>0]/sum(Geography$freq),
        type = "bar",opacity = 0.9,name='Sample') %>%
add_trace(x=Predicted.Geography$Place[Predicted.Geography$freq>0],
          y = Predicted.Geography$freq[Predicted.Geography$freq>0]/
            sum(Predicted.Geography$freq),
          type = "bar",opacity = 0.6,name='Predicted') %>%
layout(barmode='overlay', showlegend = T,xaxis = list(title=' ',
autotick = T,showticklabels = FALSE,tickcolor = toRGB("white"))
, yaxis = list(title='Distribution'))
```

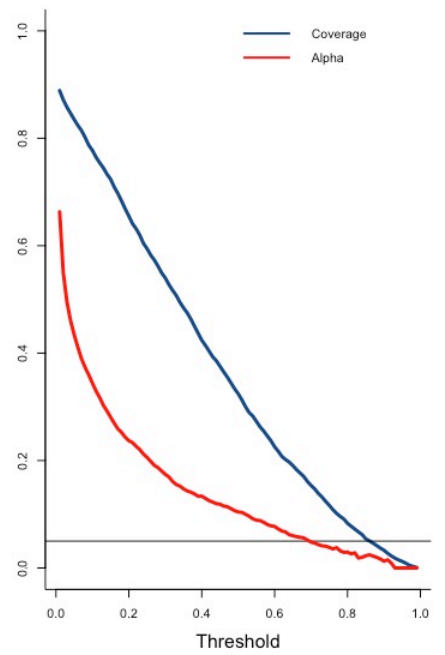
Probit Model | Coverage and Alpha



KNN Model | Coverage and Alpha



NN Model | Coverage and Alpha



Comparison Across Models

